COVARIANCE MODELS FOR MEG BRAIN SIGNALS

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Neuronal activity in the human brain is electromagnetic activity, that is, it generates both electric currents and magnetic fields. Using magneto-encephalography (MEG) the magnetic signals of the brain can be registered outside the head. The very weak magnetic field is recorded in 150 sensors in a helmet. The electric currents can be recorded using the electro-encephalography (EEG) technique. In this study we only consider recorded MEG signals.

The MEG technique is typically used in so called "evoked field experiments". In this kind of experiments a certain brain area is stimulated by an external stimulus. For example, presenting a sound can stimulate the auditory brain area. In evoked field experiments a fixed stimulus is presented several times, and the magnetic part of the brain response after each stimulus presentation is recorded using MEG. The goal is to localize the area in the brain where the response has been generated.

In order to localize the place of response generation, a model for the source of the signal is needed. The typical source model is a dipole. Assuming this dipole model with a certain amplitude time series one can calculate the predicted magnetic field strength over time on each of the 150 MEG sensors by the Biot-Savart law. In practice, one has to deal with the inverse problem, that is, estimate the dipole parameters (location and amplitude time series) based on the recorded signals. This is partly a nonlinear problem.

Solving the inverse problem is complicated by the presence of noise in the recorded signal. This noise consists of brain background activity and instrumental noise and is assumed to be Gaussian. In order to derive efficient estimators for the parameters in the model, one needs to weigh the least squares cost function by the inverse of the noise covariance matrix. This covariance matrix is unknown and has to be estimated. The noise is correlated both in space and in time. When the number of time samples is 500, the dimension of the full covariance matrix is 75000x75000. The number of stimulus repetitions is usually between 100 and 500. Hence, the sample covariance matrix will not be an adequate, non-singular estimate and parameterization of the covariance matrix is needed.

The covariance models we propose are based on Kronecker products (KP). The KP of an (nxm)-matrix A and a (pxq)-matrix B is a (np x mq)-matrix which is defined by $(A\otimes B)_{in+k,jm+l}= A_{i,k}\, B_{j,l}$ for i=1,…,n, j=1,…,m, k=1,…,p, l=1,…,q. Modelling the covariance as a single KP, $\Sigma = A\otimes B$, where A is a temporal covariance matrix and B is a spatial covariance matrix has the nice property that $\Sigma^{-1}= A^{-1}\otimes B^{-1}$.This is an advantage, since the inversion can be performed in lower dimensions. The interpretation of this parameterization is that the covariance between to noise signals is the product of a temporal factor and a spatial factor. Time and space are assumed not to be cross-correlated. The drawback of this model is that this interpretation does not comply with the nature of the background noise. A possible extension is a sum of KP of spatial and temporal covariance matrices, where each term represents a spatiotemporal process in the background noise. One can show that the full covariance matrix can be decomposed into a sum of KP. The usefulness and the goodness-of-fit of the different models will be discussed.